Nowcasting Precipitation Using Weather Radar Data for Lithuania: the First Results

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***Abstract*— Although the accuracy and the duration of modern weather forecasts constantly increase together, numerical weather prediction methods still face a few drawbacks. Due to an extensive computing time and a high power usage, these methods are unable to efficiently react to rapidly changing initial weather conditions. Also, most of the numerical weather prediction models can be less accurate for smaller regions with specific local weather conditions. These problems are addressed by a technique called nowcasting, which uses an extrapolation of various current weather conditions. Multiple research papers have shown that this technique can outperform traditional weather predictions for up to two hours. Furthermore, it can be improved using machine learning algorithms. In this paper nowcasting algorithms are used to predict a short-term precipitation over Lithuania using weather radar images provided by Lithuanian Hydrometeorology service. A Hanssen–Kuipers score is used to evaluate the accuracy of prediction against observed precipitation maps. The results of three extrapolation algorithms (basic translation, step translation, and sequence translation) and a single machine learning algorithm based on convolutional neural networks (CNN) are evaluated for two chosen hours and compared to the persistency algorithm. The average scores of each prediction algorithm for a single week are also presented. Although the results remain accurate for up to 45 minutes only, the accuracy can be improved by adding additional variables to the extrapolation. The better accuracy can also be achieved by using more sophisticated machine learning algorithms, like recurrent neural networks and their variations, that take dependencies on previous inputs in time series into account. This paper presents the first results of the algorithms, which are to be improved by further research.**

Keywords—meteorology, precipitation, forecast, nowcasting

I. Introduction

Due to the steadily growing computational capabilities of modern computers during the recent years, the accuracy and the duration of weather forecast has increased. The accuracy of the current official Day 5–7 forecasts is found to be similar to that of Day-1 forecasts from 50 years ago [1].

However, the amount of computational resources required for the evaluation of complex weather prediction models is also constantly rising. In order to achieve a weather forecast that is accurate and up to date, weather prediction services are using some of the most powerful supercomputers in the world. These computers require a high amount of power and other resources for operation and cooling.

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Moreover, the time required to collect the data from weather observation stations, to perform all the calculations and to post-process and visualize these results might take hours. Most of the weather prediction models are global and, in order to adapt these results for local conditions in their region, further processing by professionals from regional weather services from is required. This means that forecasters can fail to predict rapid changes in weather, such as sudden convective summer storms, hurricanes, and flooding, since an event may occur before forecast calculations are completed.

This issue is addressed by using a nowcasting, which is defined as the weather forecasts on very short-term period of up to 2 hours. Nowcasting is an extrapolation of current known weather conditions such as a current temperature, cloud coverage, satellite data and other parameters. A Doppler's weather radar can be used to extrapolate precipitation amplitude and location.

Nowcasting techniques are considerably faster than complex numerical weather forecast models and can be applied to predict a rapidly changing weather conditions. Nowcasting can also be used to improve existing weather forecast models by introducing more accurate data for short-term regional weather prediction and implement more precise weather alert systems that can potentially save people's lives by warning about unexpected rapidly forming storms and possible flooding.

This paper presents the first results of precipitation prediction algorithms that use weather radar images for nowcasting. The algorithms used to predict a movement of precipitation systems, use simple extrapolation and machine learning techniques, however, the obtained knowledge and results will be used to build a more complex and more accurate prediction system.

II. Related Work

In this section related work on weather data extrapolation and other short-term weather prediction methods will be discussed.

Li, Schmid, and Joss define two major extrapolation techniques: one technique tries to find the best possible fit between two different maps of radar data. The correlation

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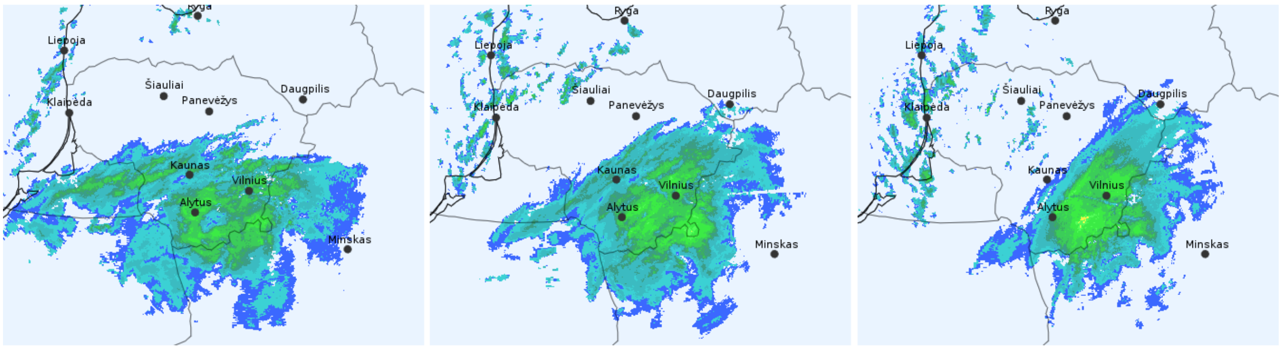

Fig. 1. The weather radar maps over Lithuania on 29/10/2017 from 11:15 to 15:15 every two hours. The blue shades indicate low rates of rain, while the green ones show a higher volume of precipitation.

coefficient is used as an objective test criterion for the agreement between the two radar patterns. The mean vector of displacement, that can be found from the observed radar pattern, allows a linear extrapolation into the future. Another group of nowcasting techniques has the ability to track and forecast the areas, the mass centroids, or other parameters of closed radar contours that represent individual convective storms or cells. Detection of a movement vector can allow further extrapolation of other storm parameters [2].

For example, Saxen et. all adapted extrapolation method to forecast thunderstorm initiation, growth, and decay. This technology is used in real-world military level applications to ensure the safety of personnel that works on the missile range [3].

Worth noting is that nowcasting and extrapolation techniques are also used for public weather prediction. It is especially useful where complex local orography and a high convectional activity limit global prediction models' accuracy. Li and Lai describe such a system in Hong Kong. Two methods are being used: the first one is object-oriented, where pixels in the radar images are grouped over some predefined intensity threshold in the form of an ellipse and tracks the movement of ellipse centroids between successive radar images. The other one derives vectors from the matching of pixel arrays (boxes) between two successive radar images through maximum cross-correlation [4].

According to Li and Lai, this system has enabled forecasters to make qualitative educated guesses of the likelihood of prolonged heavy rain or the potential of enhanced storm development. [4].

Wilson, Crook, Mueller, Sun, and Dixon in their paper Nowcasting Thunderstorms: A Status Report review the status of forecasting convective precipitation for time periods less than a few hours. In their review of nowcasting thunderstorm location by extrapolating radar echoes they state that the accuracy of these forecasts generally decreases very rapidly during the first 30 min because of the very short lifetime of individual convective cells. Fortunately, more organized features like squall lines and supercells can be successfully extrapolated for the longer time period [5].

Comparing persistency and extrapolation methods for 30 min. forecasts, Wilson et. all stated that probability of detection (POD) for persistency method is 0.13, and 0.27 for extrapolation, while false alarm ratio (FAR) is 0.85 and 0.59 respectively. These results show that extrapolation method can be significantly more accurate than a basic (often rather precise) persistency method.

Adding to what has been mentioned previously, some interesting applications of machine learning algorithms in the weather prediction area can be found. Holmstrom, Liu, and Vo implemented linear regression solution to forecast the lowest and the highest day temperature. However, the evaluation results have shown, that for a short forecast algorithm's mean squared error is almost twice as big as the error of professional forecasts [6].

Despite this, there was also some promising application: Campolo, Andreussi, and Soldati were highly satisfied with their results of predicting river flooding with a neural network model. [7].

Furthermore, Denoex and Rizand, have developed a machine learning solution based on a neural network model for a precipitation prediction from weather radar images. Authors state that, although more experiments in various meteorological situations are still needed to complete the validation of this approach, the results obtained so far are considered as highly encouraging. Their algorithm managed to outperform both persistency and extrapolation (cross-correlation) methods in short-term forecasts [8].

III. The Data

The data for this research are taken from publicly available factual weather radar maps provided by the Lithuanian Hydrometeorology service (Fig. 1).

The maps are generated every 15 minutes and indicate the observed amount of precipitation that is captured by the Doppler's weather radar. The maps cover all area of Lithuania and display a combined result of the data from two weather radars: one in Laukuva (Western Lithuania), the other in Trakų Vokė (Eastern Lithuania). Each pixel in a map represents one of 16 different levels of precipitation: a level of 0 indicates no precipitation over the area, while level 16 shows extremely high precipitation of more than 66 mm/h.

Although the precipitation data from the weather radars can be interpreted as an actual observed rainfall in a given area, there are some limitations that should be considered. First of all, the weather maps do not differentiate between the types of precipitation. Whether it is rain, snow, or hail, it will have the same representation in a map. Secondly, the further an area is from a radar, the lower resolution is available. Although such decrease in resolution is not significant for Lithuania, it might result in a lower accuracy for the regions that are further away from the radars. Not every object detected by a radar is precipitation. For example, mountains, high buildings, wind farms [9] or even bird migration [10] can be mistaken for a rain or block a field of view to the actual precipitation.

In this research, weather radar data from the date range of 23/10/2017 to 30/10/2017 will be used for the evaluation of algorithms. This week contains three major precipitation events and periods without rain between them.

The radar images over Lithuania are available at a maximum resolution of 768 by 768 pixels, but due to performance reasons (especially for machine learning algorithms), all images are scaled down to a resolution of 64 by 64 pixels.

Convolutional neural network (CNN) based algorithm was trained with 10 000 sets of weather radar images, that were retrieved between 01/11/2017 and 25/04/2018. The data used for training of the network was not used during the evaluation.

IV. Evaluation of Accuracy

Evaluating the accuracy of precipitation forecast is rather a challenge. A forecast is accurate only if predicted precipitation closely matches an actual observed rainfall amount. In this research, weather radar images are used both as prediction source and as an evaluation.

To compare the similarity between two images, one can use a traditional root mean square error algorithm, where the difference between actual and observed precipitation amount is calculated. However, the results of this error function have no clear boundaries and it is hard to evaluate how accurate forecast actually is.

For this reason, the Hanssen–Kuiper's (HK) score, also known as the true skill statistic, is used in this paper. This score describes the performance of a classification model and is widely used for forecast verification [11].

First, each grid-point (pixel) in an actual and predicted precipitation map is classified into four categories: correct non-rain forecasts (Z), false alarms (F, precipitation in a certain area was predicted, but did not occur), misses (M, the precipitation was not predicted, but did occur), or hits (H, a precipitation event was predicted successfully).

From the number of grid points in each category, it is possible to calculate the HK score using Equation (1).

$$HK = \frac{(ZH-FM)}{(Z+F)(M+H)} \tag{1}$$

This score can fall between 0 and 1, where a score of 1 indicates an ideal forecast.

However, the HK score only uses the occurrence of a rain event without taking the strength of precipitation into account. This means that a predicted rainfall amount of 1 mm/h, while the actual was 30 mm/h, would be considered as a hit. Furthermore, only respective pixels in an actual and predicted image are compared. If a rainfall did actually occur, but just a few pixels away, this would be considered as a miss or a false alarm.

These problems can be addressed by introducing the precipitation strength thresholds during the classification and by increasing a score for near misses. Nevertheless, this research is oriented to a comparison of different algorithms only and any adjustments of score would be unnecessary.

V. Algorithms

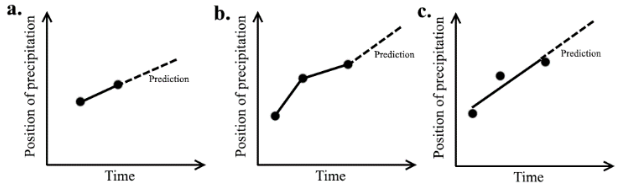

Fig. 2. The extrapolation of precipitation position by the basic translation algorithm (a), step translation algorithm (b) and sequence translation algorithm (c).

In this section precipitation prediction algorithms, used in this research, will be presented. Translation algorithms work by extracting precipitation movement vector from consequent weather radar images and extrapolating them into the future. These algorithms differ in the way how a movement vector is extracted.

The CNN-based algorithm uses machine learning techniques to predict subsequent weather radar images in the future.

A. Persistency

Persistency algorithm is an assumption that all the initial conditions will remain stable in the future. This means that persistency algorithm returns the initial weather radar image for every period of a forecast. Such technique is commonly used in weather prediction accuracy evaluations as a benchmark. If an accuracy of a weather prediction algorithm is lower than the one with persistency assumption, the quality of an algorithm is poor.

B. Basic translation algorithm

Basic translation algorithm takes two consequent weather radar images and finds an anticipated precipitation movement vector between them. Using this vector, an arbitrary amount of radar images can be generated by performing an image translation at each forecast step (Figure 2, a.).

The algorithm uses brute force to find a horizontal and a vertical pixel offset at which a correlation value between the two images is the highest. A HK score, defined in the fourth chapter, is used as a correlation value.

C. Step translation algorithm

It might not always be possible to find an accurate precipitation movement vector from just the two consequent images. Furthermore, movement vector can only have integer values. These problems are addressed with a step translation algorithm.

This algorithm takes four consequent weather images and computes the best movement vector for each adjacent pair of two images with the same method as in the basic translation algorithm. Then an average of these vectors is obtained and used as the final best movement vector from which the forecast images are generated. (Fig. 2, b.)

Since the obtained average vector can have non-integer values (and it is impossible to move an image with a non-integer offset of pixels without using additional transformation), both source image and vector itself are scaled up by the same factor to perform translation with integer values. After this process, the image is resized down to its original resolution.

D. Sequence translation algorithm

Although step translation algorithm ensures that a precipitation movement vector is obtained more accurately, there still might be errors while determining movement direction between two weather radar images.

The sequence algorithm, same as the step translation algorithm, uses four radar images to determine the direction of precipitation, but this algorithm computes the best movement vector for the whole sequence at once (Figure 2, c). Sequence translation algorithm computes a sum of the HK scores for each pair of adjacent images at every possible translation vector value. The best movement vector is determined by the highest sum of the HK scores.

E. CNN-based algorithm

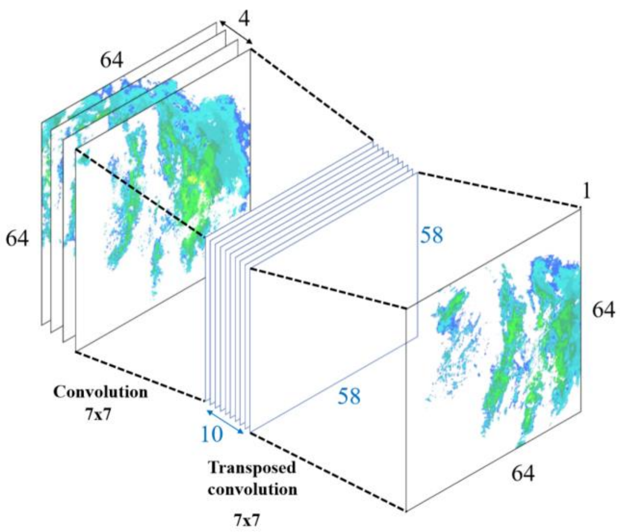

Fig. 3. The architecture of CNN-based prediction algorithm. Network uses convolution and transposed convolution to predict the next image from four previous weather radar images.

This algorithm is based on an architecture of a convolutional neural network (Figure 3). It consists of three layers of neurons.

Input layer receives four subsequent weather radar images with a resolution of 64 x 64. Each image in a sequence is represented as a different channel of an input (similarly to how RGB color channels are represented in an ordinary image).

Next, convolution is applied between the input and the hidden layer, using a kernel with a size of 7 x 7, which reduces the resolution of the images in the hidden layer to 58 x 58. The number of channels in the hidden layer is expanded to 10. The kernel size of 7 x 7 was selected to capture the possible movement of precipitation between the first and the fourth input images in a single kernel. 10 channels in the hidden layer yielded the best results during the experiments.

Finally, a transposed convolution (sometimes called deconvolution) is applied between the hidden and the output layer with a single channel. This transforms an image into the original resolution of 64 x 64. Resulting image is an output of a neural network and represents generated map of precipitation for the next time step after four input images.

The architecture of this neural network can only predict a single weather radar image into the future. To generate an arbitrary amount of result images, each output of the network is passed into the input of the next iteration, which generates precipitation image for the subsequent time step.

VI. Single Experiment Results

A precipitation event of 29/10/2017 was selected to compare the results of the prediction algorithms. Weather radar image obtained at 09:45 AM local time, together with three previous images, was used as a source image. Every algorithm predicted two hours of precipitation into the future.

Figure 4 displays a forecasted precipitation with all the algorithms mentioned above, together with actual observed conditions. An HK score, that determines the accuracy of every forecast when compared with the actual precipitation, is displayed under each predicted image.

For this precipitation event, the CNN-based algorithm outperformed every other algorithm, including persistency benchmark. Its HK score was the highest at almost every step of the forecast. In fact, for this particular event, only Basic translation algorithm failed to outperform persistency benchmark.

Every algorithm obtained different best precipitation movement vector: a pixel offset of [0, 1] was obtained by the basic translation algorithm, [0.25, 0.5] by the step translation algorithm and [1, 0] by the sequence translation algorithm. Positive x values indicate movement to the east and positive y values to the south.

Translation algorithms try to predict only the movement of precipitation, without considering changes in strength and shape, but can still yield reasonably accurate results for the first hour of the forecast. On the other hand, CNN-based algorithm managed to predict that precipitation system will rotate counter-clockwise during this particular event and maintained rather accurate evaluation of possible precipitation strength in the area.

However, the CNN-based algorithm has lost some precipitation shape details during the longer forecast and predicted rather smooth contour in contrast to the actual more scattered shape.

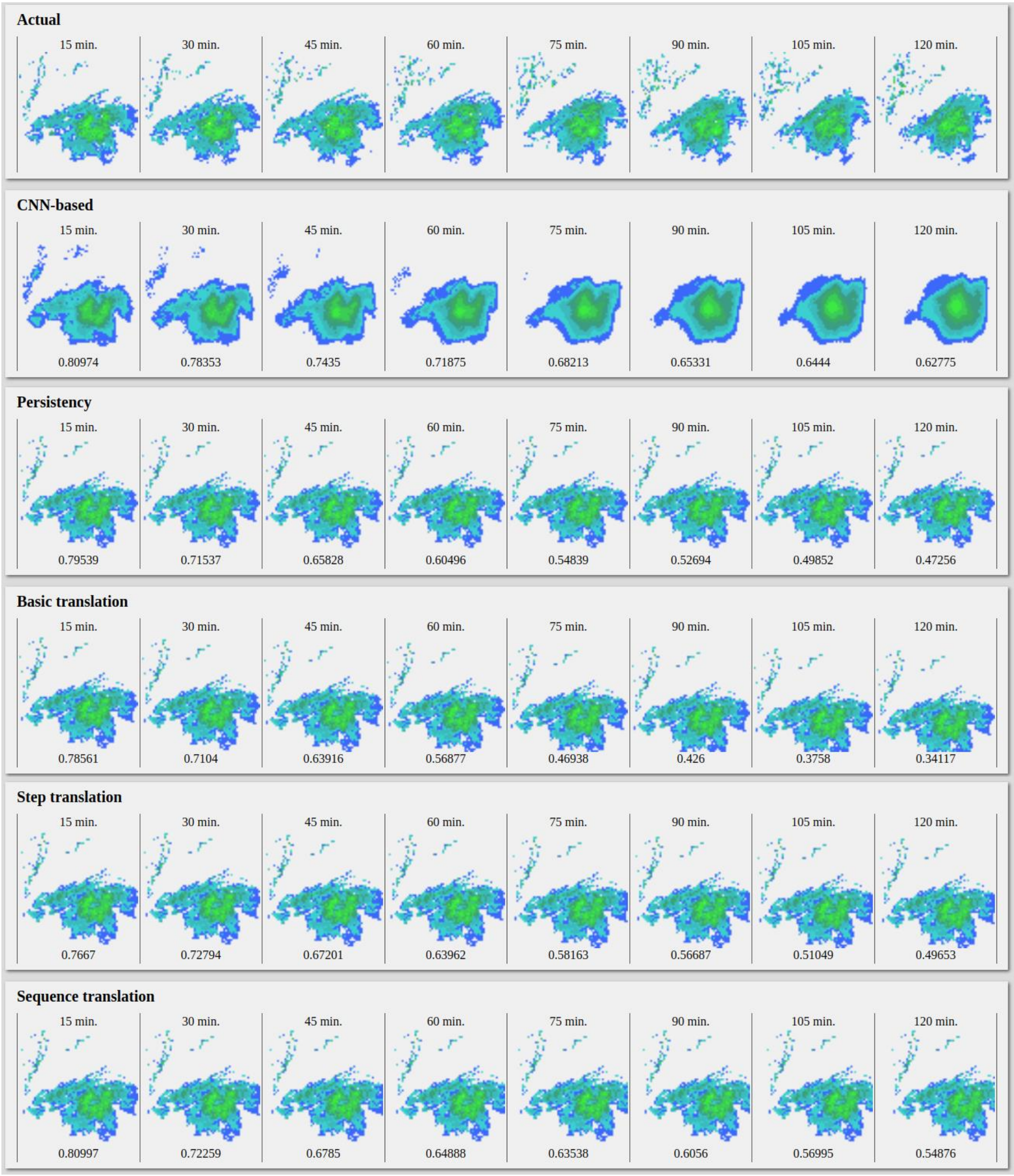

Fig. 4. The algorithm results for a precipitation event of 29/10/2017 09:45 AM. Each row consists of a set of images for up to 2 hours with 15 minutes intervals, generated by each algorithm. The number below each image indicates an evaluated HK accuracy score.

The basic translation algorithm failed to obtain a correct direction to which precipitation was moving. This indicates that two consequent images are not always enough to correctly calculate the movement direction.

VII. Averaged Results

To compare the accuracy of the algorithms for a longer period, a week of 23/10/2017 to 30/10/2017 was chosen. Every algorithm generated 8 weather prediction images for two hours into the future at 15 minutes intervals. Generated images were compared with an actual precipitation to obtain an HK for each pair of the images. Then, the average scores for every step of the forecast were calculated. The comparison of an accuracy of the algorithms is displayed in Figure 5.

Comparison results show that CNN-based algorithm outperforms every other algorithm for almost two hours of the forecast. Sequence translation algorithm was the most accurate among the extrapolation algorithms and exceeded precipitation benchmark for the first 90 minutes of the forecast.

The step translation and the basic translation algorithms performed poorly. Their accuracy was much lower than the persistency benchmark score for the forecasts longer than 30 minutes.

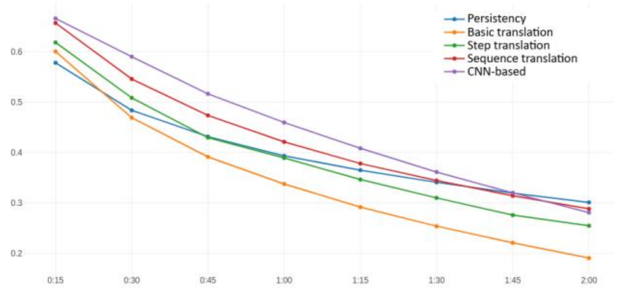

Fig. 5. The comparison of the HK score of the algorithms for a week of 23/10/2017 to 30/10/2017. *x* axis defines the duration of the forecast; *y* axis – HK prediction accuracy score.

Nonetheless, the prediction accuracy of every algorithm decreases rapidly, and the only CNN-based algorithm has an accuracy higher than 0.5 at 45 minutes forecast. However, as explained in the fourth chapter, selected method of HK score evaluation does not include additional scores for near misses, when precipitation is predicted correctly with an offset of a few pixels.

VIII. Conclusions and future work

In this research, it was shown that precipitation movement extrapolation algorithm can outperform persistency benchmark if movement direction is obtained correctly. In addition to this, even a simple convolutional neural network can predict movement and changes in precipitation shape reasonably well for a short period of time. However, the accuracy of a prediction decreases rapidly and can't be trustworthy for periods longer than an hour.

Presented precipitation translation algorithms are very simple and do not take the precipitation rain strength into account. The extrapolation of these additional values may help to increase prediction accuracy. The translation of rotation was also tested, however reasonable accuracy was not reached because algorithms were unable to correctly determine rotation direction.

Furthermore, although CNN-based algorithm performed the best, is not the most suitable machine learning algorithm to predict changes in time, since it has no memory of the previous inputs, which might be important when predicting precipitation further into the future. There are better neural network architectures to tackle this problem, like Recurrent Neural Networks (RNN) or Long Short-Term memory (LSTM) networks. In addition to this, movement vectors obtained with extrapolation techniques can be used as additional features to improve machine learning accuracy.

Finally, the accuracy of official precipitation forecasts should also be evaluated to better understand how extrapolation and machine learning prediction accuracy compares to numerical forecasts.

This research is still at a very early stage and presents only the basic algorithms, however, a broad spectrum of available techniques in this area (such as the inclusion of rain strength extrapolation, or various more sophisticated machine learning methods for prediction of time series) will allow further improvements in the forecast accuracy and duration.

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